In [173…
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [174…
```
import io
%cd "/Users/rajeshprabhakarkaila/Desktop/Datasets/MovieLens"
```

```
/Users/rajeshprabhakarkaila/Desktop/Datasets/MovieLens
```

In [175…
```
moviesdf=pd.read_csv("movies_metadata.csv",low_memory=False)
```

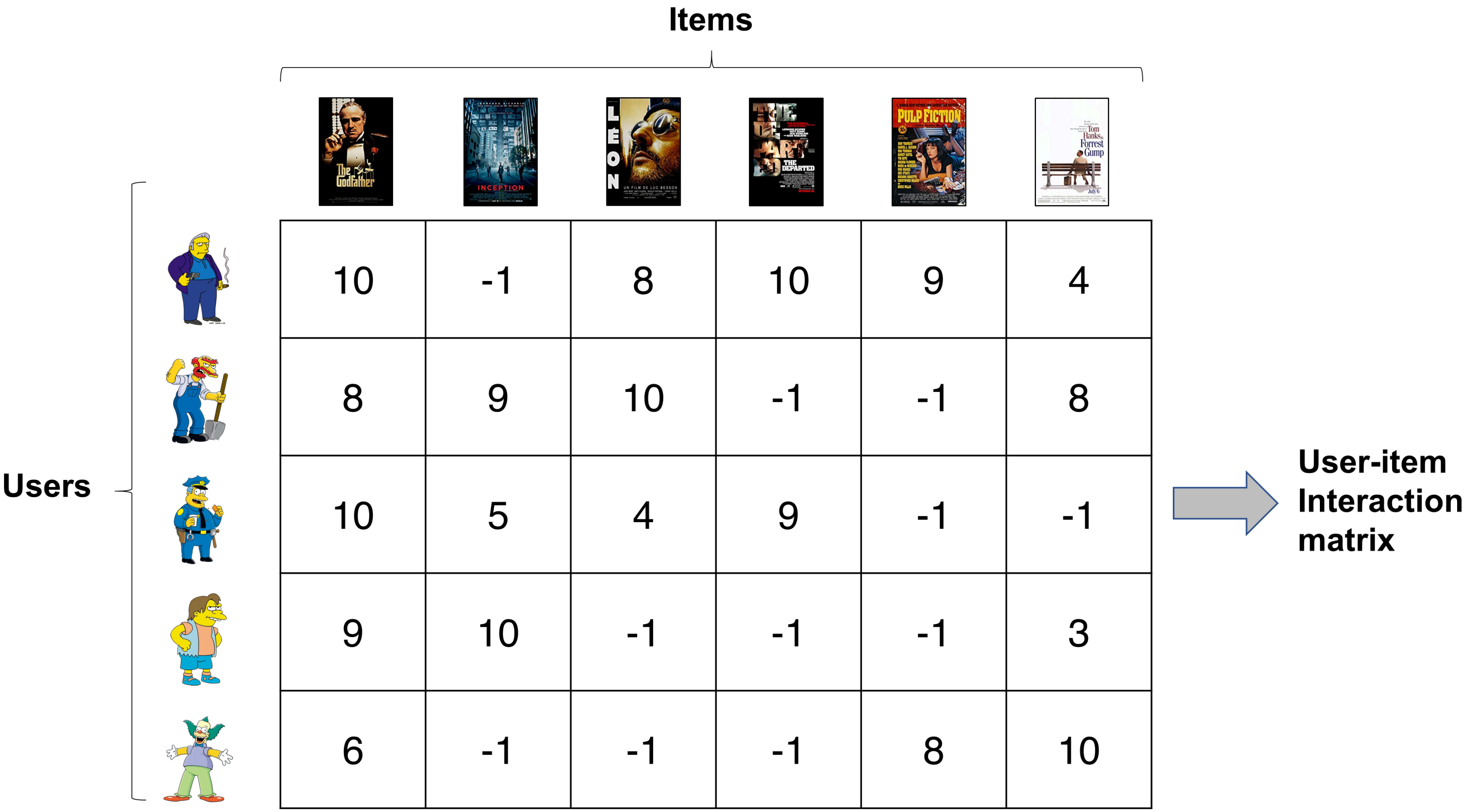
In [176…
```
ratingsdf=pd.read_csv("ratings_small.csv")
```

In [177…
```
# Recommender Systems or Recommendation Engines - Suggest similar items based on profile,
# pattern, usage, feedback, etc.

# 2 Types of Recommender systems that are widely used are
# 1) Collaborative Filtering - Recommendations are based on similarity measures like ratings
# between users and items. Basic assumption is users with similar interest will have
# common preferences.
# Collaborative Filtering uses a User Item Matrix to generate recommendtations. The matrix
# contains values that indicate user preferences to a particular item.

# Users Prefernces can be both
# a) Explicit Feedback - Ratings, Scores, Stars, Votes, Reviews(text), etc.
# b) Implicit Feedback - Indirect user behavior like number of times watched, number of
# times saved, recommendation sharing, etc.

# 2) Content Based Recommendation System - Content like reviews, description/overview,
# customer feedback etc. in form of text. Natural Language Processing techniques are used
# in this recommender systems
```



In [179…
```
moviesdf['id'].head(3)
```

Out[179…
```
0      862
1     8844
2    15602
Name: id, dtype: object
```

In [180…
```
ratingsdf['movieId'].head(3)
```

Out[180…
```
0      31
1    1029
2    1061
Name: movieId, dtype: int64
```

In [181…
```
# rename column movieId as id for merging both dataframes
ratingsdf.columns=['userId','id','rating','timestamp']
```

In [182…
```
#convert it to numeric in moviesdf
moviesdf['id']=pd.to_numeric(moviesdf['id'],errors="coerce")
```

In [183…
```
# Inner Join of both dataframes
moviesdf_merge=moviesdf.merge(ratingsdf,on="id")
```

In [184…
```
moviesdf_merge.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 44994 entries, 0 to 44993
Data columns (total 27 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   adult                  44994 non-null  object
 1   belongs_to_collection  10793 non-null  object
 2   budget                 44994 non-null  object
 3   genres                 44994 non-null  object
 4   homepage               10959 non-null  object
 5   id                     44994 non-null  float64
 6   imdb_id                44994 non-null  object
 7   original_language      44994 non-null  object
 8   original_title         44994 non-null  object
 9   overview               44857 non-null  object
 10  popularity             44994 non-null  object
 11  poster_path            44958 non-null  object
 12  production_companies   44994 non-null  object
 13  production_countries   44994 non-null  object
 14  release_date           44965 non-null  object
 15  revenue                44994 non-null  float64
 16  runtime                44990 non-null  float64
 17  spoken_languages       44994 non-null  object
 18  status                 44993 non-null  object
 19  tagline                31516 non-null  object
 20  title                  44994 non-null  object
 21  video                  44994 non-null  object
 22  vote_average           44994 non-null  float64
 23  vote_count             44994 non-null  float64
 24  userId                 44994 non-null  int64
 25  rating                 44994 non-null  float64
 26  timestamp              44994 non-null  int64
dtypes: float64(6), int64(2), object(19)
memory usage: 9.3+ MB
```

In [185…

```
# Create User Item Matrix using pivot_table()
user_item_matrix=moviesdf_merge.pivot_table(index=['userId'],columns=['title'],
                                              values="rating",aggfunc="mean").fillna(0)

# User Item Matrix is sparse matric that has many zeroes
```

In [186…
```
# To check which movies are rated by usedId 10
user10_rate=user_item_matrix.loc[10]
print(len(user10_rate[user10_rate>0].index.tolist()))
```

```
21
```

In [187…
```
print(user10_rate[user10_rate>0].index.tolist())
```

```
['A Brief History of Time', 'A Very Long Engagement', 'André Hazes, Zij Gelooft in Mij', 'Bang, Boom, Bang', 'Dr. Je
kyll and Mr. Hyde', 'Eyes Wide Shut', 'Hostel', 'Marie Antoinette', 'Point Break', 'Princesses', 'Spanglish', 'Star
Trek: The Motion Picture', 'Teenage Mutant Ninja Turtles III', 'The Addams Family', 'The Breakfast Club', 'The Conve
rsation', 'The Million Dollar Hotel', 'The Miracle of Bern', 'The Soft Skin', 'The Three Musketeers', 'Twin Peaks: F
ire Walk with Me']
```

In [188…
```
user_item_matrix.shape
```

Out[188…
```
(671, 2794)
```

In [189…
```
moviesdf_merge['vote_count'].groupby(moviesdf_merge['title']).sum().nlargest(20)
```

Out[189…
```
title
Titanic                                                    1144980.0
Men in Black II                                             714112.0
Terminator 3: Rise of the Machines                          705348.0
Reservoir Dogs                                              584613.0
Jurassic Park                                               564984.0
Back to the Future Part II                                  557492.0
Star Wars                                                   555796.0
Scarface                                                    356006.0
A Clockwork Orange                                          350064.0
Rain Man                                                    348876.0
Batman Returns                                              341200.0
Donnie Darko                                                332382.0
Ocean's Eleven                                              309824.0
The Bourne Supremacy                                        304538.0
Harry Potter and the Prisoner of Azkaban                    301850.0
Psycho                                                      300625.0
Back to the Future                                          299472.0
Batman Begins                                               292929.0
Pirates of the Caribbean: The Curse of the Black Pearl      273258.0
Cars                                                        271388.0
Name: vote_count, dtype: float64
```

In [190…
```
# Different Methods are used for identifying collaborative similarity
# 1) Nearest Neighbors (Euclidean Distance) ;2) Singular Value Decomposition
# 3) Non Matrix Factorization
```

In [191…
```
from sklearn.neighbors import NearestNeighbors
```

In [221…
```
cf_nn_model=NearestNeighbors(metric="euclidean",algorithm="brute",n_neighbors=10,
                             n_jobs=-1).fit(user_item_matrix.T)
```

In [223…
```
def get_recommend(movie_title, n_recommends=10):
    if movie_title not in user_item_matrix.columns:
        return "Movie not found"

    movie_idx = user_item_matrix.columns.get_loc(movie_title)

    # Ensure input shape is correct
```

```
    distances, indices = cf_nn_model.kneighbors(
        user_item_matrix.T.iloc[movie_idx].values.reshape(1, -1),
        n_neighbors=n_recommends + 1  # +1 to exclude itself
    )

    # Fix: Use columns (movie titles) instead of index
    recommended_movies = [user_item_matrix.columns[i] for i in indices.flatten()[1:]]  # Skip itself
    return recommended_movies
```

In [225…

```
get_recommend('The Matrix')
```

Out[225…

```
['Shock Treatment',
 'King of California',
 'The Matrix',
 'Fire Birds',
 'Life',
 'Snow White and the Seven Dwarfs',
 'My Best Fiend',
 'Alive',
 "It Happened at the World's Fair",
 'Highlander']
```

In [229…

```
# Content Based Recommender System
moviesdf['overview']=moviesdf['overview'].fillna("")
```

In [231…

```
moviesdf['overview']=moviesdf['overview'].str.lower()
```

In [233…

```
from sklearn.feature_extraction.text import CountVectorizer
```

In [235…

```
DTM=CountVectorizer(max_features=200,stop_words="english",ngram_range=(2,2))
```

In [237…

```
X_DTM=DTM.fit_transform(moviesdf['overview'])
```

In [239…

```
from sklearn.metrics.pairwise import linear_kernel
```

In [241…

```
cosine_sim=linear_kernel(X_DTM,X_DTM)
```

In [243…

```
indices=pd.Series(moviesdf.index,index=moviesdf['title']).drop_duplicates()
```

In [245…
```python
def get_recommend(title,cosine_sim=cosine_sim):
    idx=indices[title]
    sim_scores=list(enumerate(cosine_sim[idx]))
    sim_scores=sorted(sim_scores,key=lambda x:x[1],reverse=True)
    sim_scores=sim_scores[1:11]
    movie_indices=[i[0] for i in sim_scores]
    return moviesdf.title.iloc[movie_indices]
```

In [281…
```python
get_recommend("Jumanji")
```

Out[281…
```
4746                          Thir13en Ghosts
12169    The Diving Bell and the Butterfly
13029                               Quarantine
17260                                  Private
20153                                Extracted
31835                           The Last Light
34346                               Septic Man
43127                                  The Bar
21345                            The Last Days
40600                        Terminal Invasion
Name: title, dtype: object
```

In [251…
```python
# Hybrind Model - Both Content Based with Singular Value Decomposition
from sklearn.feature_extraction.text import TfidfVectorizer
```

In [263…
```python
tfidf=TfidfVectorizer(max_features=3000,stop_words="english",ngram_range=(2,2))
```

In [265…
```python
X_tfidf=tfidf.fit_transform(moviesdf['overview'])
```

In [266…
```python
from sklearn.decomposition import TruncatedSVD
```

In [267…
```python
svd=TruncatedSVD(n_components=100,random_state=42)
```

In [268…
```python
svd_matrix=svd.fit_transform(X_tfidf)
```

In [273…
```python
from sklearn.metrics.pairwise import cosine_similarity
```

In [275…
```
cosine_sim=cosine_similarity(svd_matrix)
```

In [277…
```
def get_recommend(title,cosine_sim=cosine_sim):
    idx=indices[title]
    sim_scores=list(enumerate(cosine_sim[idx]))
    sim_scores=sorted(sim_scores,key=lambda x:x[1],reverse=True)
    sim_scores=sim_scores[1:11]
    movie_indices=[i[0] for i in sim_scores]
    return moviesdf.title.iloc[movie_indices]
```

In [279…
```
get_recommend("Jumanji")
```

Out[279…
```
4746                        Thir13en Ghosts
12169    The Diving Bell and the Butterfly
13029                           Quarantine
17260                              Private
20153                            Extracted
31835                       The Last Light
34346                           Septic Man
43127                              The Bar
21345                        The Last Days
40600                    Terminal Invasion
Name: title, dtype: object
```

In [ ]: